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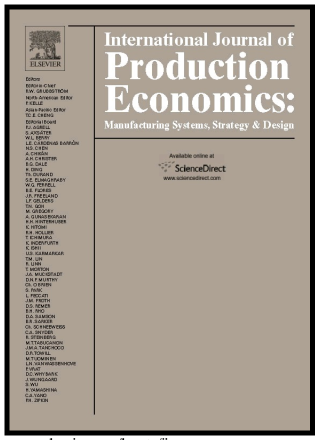

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Abstract

The emergency supply of blood in natural and anthropogenic disasters has proved challenging. This article presents a stochastic bi-objective supply chain design model for the efficient (cost minimizing) and effective (delivery time minimizing) supply of blood in disasters. The blood supply network under investigation is comprised of blood donors, mobile blood facilities, local and regional blood centers, and demand points. A hybrid solution approach, combining the ε-constraint and Lagrangian relaxation methods, is developed to solve the proposed model. Our numerical experiments and subsequent discussions focus on (1) investigating the utility of the proposed model in solving different size problems, (2) exploring possible tradeoffs between supply chain cost and delivery time, (3) identifying the areas along the supply chain where investments can be made to improve supply chain efficiency and effectiveness, and (4) performance benchmarking of the proposed stochastic programming approach.

Keyword: Humanitarian aid supply chain; Disaster relief operations; Blood supply; Supply chain design; Stochastic; ε-constraint method; Lagrangian relaxation method.

1. Introduction

On 26 December 2003, a 6.6 M_L earthquake devastated the historical city of Bam in southeastern Iran. Over 30,000 people were killed, 30,000 injured, and 85% of buildings destroyed or severely damaged (Eshghi and Zare, 2003; USGS, 2003). The disaster caused serious infrastructure damage, and disrupted land transportation and utility supply systems. All health facilities in the area were destroyed with over 50% of health personnel reported killed or missing. Overburdened with the influx of injured people, many hospitals around the country called for urgent supply of blood units for emergency surgical needs. Yet, from over 100,000 donated blood units, only about 21,000 units were actually received and utilized by these hospitals (Abolghasemi et al., 2008). The Bam experience revealed the scale and significance of the required relief effort, and in particular the management of blood supply, in the aftermath of disasters. Since 2003 Bam earthquake, the world has witnessed several other natural disasters such as 2004 Indian Ocean earthquake and tsunami, the 2008 China earthquake, the 2010 Haiti earthquake, the 2011 Japan earthquake and tsunami, the 2013 Philippines storms, and the 2013 Pakistan earthquake, reinforcing similar relief distribution implications.

Apart from these natural disasters, anthropogenic catastrophes have also caused unexpected deaths and injuries. Numerous examples of anthropogenic disasters exist, such as the September 11 attacks in the U.S., the 2008 Mumbai attacks, and the 2013 Boston Marathon bombings. On these occasions, many injured victims are in urgent need of blood products. While the lack of blood and blood donors has barely been a problem in such mass casualty events, ineffective distribution and untimely supply of blood to hospitals could wreak havoc (Gerberding et al., 2007). In the two months following the September 11 attacks, the blood collected was reported to be double the normal rate, but a large portion was never utilized due to limits in effectively storing and distributing the donated blood (Congress House Committee on Energy and Commerce, 2002). Similarly, the 1998 terrorist attack in Nairobi revealed blood supply deficiencies in Kenya (PEPFAR, 2006).

The aforementioned examples indicate the need for blood supply chain solutions that enable hospitals and medical system infrastructures to respond more effectively to mass casualty events (Gerberding et al., 2007; Williamson and Devine, 2013). Sri Lanka's nationally coordinated blood distribution network has been able to utilize its available blood resources through effective communication and transportation between facilities and mobilization of its available bloodstocks (Kuruppu, 2010). However, even the more developed countries have shown to be unprepared for major disasters due to inadequate infrastructures (Starr and Van Wassenhove, 2014).

One primary issue in disaster relief modeling efforts, including blood supply chain modeling, is the extremely uncertain and dynamic decision environment (Mete and Zabinsky, 2010; Starr and Van Wassenhove, 2014). In addition, there is a need to incorporate multiple performance measurement and management objectives in addition to the classical financial objectives. Several studies have dealt with designing the right objective functions when it comes to the delivery of relief supplies in disasters (Gralla et al., 2014). Yet, the design of objective functions and constraints has been debated for many years (Starr and Van Wassenhove, 2014).

In this paper, we present a stochastic bi-objective supply chain design model for the timely and efficient supply of blood in disasters. The *"time"* element addresses the urgent need for blood supply, whereas *"efficiency"* concerns minimization of operational costs. We study a realistic and relatively complex blood supply network, the chains of which include blood donors, mobile blood facilities (such as blood donation vehicles), local blood centers, regional blood centers, and hospitals. A hybrid solution approach combining the ε-constraint and Lagrangian relaxation methods is developed to solve the bi-objective model. The performance of the proposed model and solution method is then investigated in a number of numerical experiments and the results are discussed in detail.

2. Literature Review

The challenge of getting supplies and services to the affected people in disasters falls within the scope of humanitarian aid supply chain management (Wassenhove, 2006). Often treated as a subset of humanitarian aid supply chains, disaster relief operations involve the emergency delivery of food and medical supplies to injured victims immediately after a disaster occurs. Many humanitarian supply chains often operate on some advanced warning (and sometimes on a permanent ongoing activity, like food bank supply chains). Disaster relief operations by contrast rely on the existing infrastructure for fast delivery of emergency products and services with no or little prior notice (Whybark et al., 2010). This being said, a high degree of uncertainty and short lead-times are the primary characteristic of disaster relief supply chains.

Modeling efforts, mainly optimization and simulation models, have tried to address some of the disaster relief supply chain challenges (see for example Gralla et al. (2014); Özdamar and Demir (2012); Sheu (2007, 2010)). Caunhye et al. (2012) classify the published emergency logistics optimization models into 'facility location' and 'relief distribution and casualty transportation' models. They also provide additional classifications under each of these two main categories. Cost minimization and evacuation time minimization are identified as the predominant objective functions in facility location models (which also define the scope of the current study). The latter include 'location-evacuation models' and 'location models with relief distribution and stock prepositioning'. None of the reviewed papers falls within the scope of emergency blood supply in disasters.

A generic review of blood inventory and supply chain management studies was completed by Beliën and Forcé (2012) focusing on different types of blood products, planning levels, and solution methods. Modeling efforts that focus on strategic design of blood supply networks are scarce. Daskin et al. (2002) and Shen et al. (2003) present nonlinear integer programing models for a single-period joint location-inventory blood supply problem. The models aim to simultaneously determine the number and location of distribution centers and the inventory levels at each center. Heuristic solution methods are developed to solve the proposed models. Şahin et al. (2007) develop a single-period location-allocation model for regionalization of blood services in a hierarchical network consisting of regional blood centers, blood stations, and mobile facilities. A location-allocation and scheduling model for the supply of emergency blood in the aftermath of earthquakes in Beijing was developed by Sha and Huang (2012). The model aims to minimize the total operational costs over a given planning horizon. The most recent study in this context is the work of Jabbarzadeh et al. (2014) who present a robust network design model for determining blood facility location-allocation decisions during multiple post-disaster periods. The goal is to design a network for the cost-effective delivery of blood products to hospitals while ensuring that the network is robust to major disruptions.

To the best of our knowledge, a modeling effort for blood supply chain network design considering tradeoffs between multiple delivery goals is non-existent. One general reason could be the difficulty of solving supply chain design and planning models with conflicting objectives (Fahimnia et al., 2015a; Fahimnia et al., 2015b; Jabbarzadeh et al., 2015). Using expert opinions, Gralla et al. (2014) identify five key attributes as general aid delivery goals. These include the amount of aid delivered, commodity type prioritization, delivery location prioritization, the speed of delivery, and the operational cost. While one would realize the importance of all these attributes in the general context of humanitarian aid supply chain management, we also emphasize that the choice of these goals and their degree of significance may vary depending on the type and nature of aid and supply chain structure. For example, delivery lead-time may play a key role in the emergency blood supply as delayed delivery is very likely to contribute to an increased mortality rate. Alternatively, design and establishment of supply networks usually incur substantial irreversible costs (Esmaeilikia et al., 2014; Zokaee et al., 2014) and hence a cost minimization goal cannot be neglected, especially in current context of uncertain and shrinking infrastructure funding (Starr and Van Wassenhove, 2014). Therefore, a tradeoff between delivery speed and cost of designing and establishing a blood supply chain can be of paramount importance. This is what we try to accomplish in this paper.

This paper contributes to the area of blood supply network design in the following ways. First, we present a stochastic bi-objective supply chain network design model for the efficient (cost minimizing) and effective (delivery time minimizing) supply of blood in disasters. Second, we study a realistic blood supply chain network that incorporates blood donors, mobile blood facilities, local blood centers, regional blood centers, and hospitals. Third, we present a hybrid solution approach that combines an ε-constraint method (converting the bi-objective model into a single-objective model) with a Lagrangian relaxation method (finding an optimal solution to the unified optimization model). A number of numerical tests are conducted to investigate (1) the performance of the proposed hybrid solution method, (2) possible tradeoffs between supply chain cost and delivery time, (3) sensitivity of the numerical results to changes in the key input parameters, and (4) the benefits of the two-stage stochastic programming approach.

3. Model Development

3.1 Problem statement

The supply chain under investigation comprises blood donors, mobile blood facilities, local blood centers, regional blood centers, and demand points including hospitals and medical centers. The location of mobile blood facilities (such as blood donation vehicles) may vary from one period to another. Blood can be donated at either a mobile blood facility or a blood center within a certain geographical distance, but not at the regional blood centers. The blood collected in mobile blood facilities is shipped to local blood centers and regional blood centers where the blood transfusion process is completed. These centers will then fulfill the blood demand of hospitals and medical centers. Regional blood centers are capable of providing all transfusion processes and services, but local blood centers may not offer a full range of services. In such cases, some of the transfusion processes of a local blood center may be directed to a pre-assigned regional blood center. The referral rate is the rate of services directed by a local blood center to a regional blood center.

The problem is formulated as a bi-objective stochastic model to design an emergency blood supply chain resilient to different disaster scenarios. The first objective minimizes the total supply chain costs including the cost of locating mobile blood facilities, the cost of moving mobile blood facilities, operational cost at blood facilities, transportation cost and inventory holding cost. The second objective minimizes the average delivery time from mobile blood facilities to hospitals. The model aims to determine the following decisions at each period of the planning horizon:

- The number of mobile blood facilities to be located;
- The location of mobile blood facilities under each scenario;
- The quantity of blood to be collected at each facility under each scenario;
- The quantity of blood to be transported from mobile blood facilities to local and regional blood centers under each scenario,
- The quantity of blood to be transported from local blood centers to regional blood centers under each scenario,

- The blood inventory level in local and regional blood centers at the end of each period under each scenario; and
- The quantity of blood transported from local and regional blood centers to hospitals under each scenario.

3.2 Parameters and decision variables

The following indices, parameters and decision variables will be used for the purpose of model formulation.

Indices:

I	Set of donor groups indexed by i
J	Set of candidate locations for mobile blood facilities indexed by j
K	Set of local blood centers indexed by k
R	Set of regional blood centers indexed by r
H	Set of hospitals and medical centers indexed by h
S	Set of disaster scenarios indexed by s
T	Set of time periods indexed by t

Parameters:

f	Fixed cost of establishing a mobile blood facility
v_{jlt}^{s}	Cost of moving a mobile blood facility from location l to location j in period t under scenario s
o_{ijt}^{s}	Unit operational cost at mobile blood facility j from donor group i in period t under scenario s
ob^{s}_{kt}	Unit operational cost at local blood center k in period t under scenario s
$0\,r^{s}_{r\,t}$	Unit operational cost at regional blood center r in period t under scenario s
ab_{jkt}^{s}	Unit transportation cost from mobile blood facility j to local blood center k in period t under scenario s

ar_{jrt}^{s} Unit transportation cost from mobile blood facility j to regional blood center r in period t under scenario s

abr^{s}_{kr} Unit transportation cost from local blood center k to regional blood center r in period t under scenario s

arh^{s}_{kht} Unit transportation cost from local blood center k to hospital h in period t under scenario s

abh^{s}_{rht} Unit transportation cost from regional blood center j to hospital h in period t under scenario s

hb_{kt} Unit holding cost at local blood center k in period t

hr_{rt} Unit holding cost at regional blood center r in period t

d_{ht}^{s} Blood demand at hospital h in period t under scenario s

tb_{jk} Travel time from mobile blood facility j to local blood center k

tr_{jr} Travel time from facility j to regional blood center r

tc_{kr} Travel time from local blood center k to regional blood center r

tq_{rh} Travel time from regional blood center r to hospital h

tp_{kh} Travel time from local blood center k to hospital h

b Capacity of a mobile blood facility

cb_{k} Storage capacity of local blood center k

$c\ r_{r}$ Storage capacity of regional blood center r

m_{i}^{s} Maximum blood supply of donor group i under scenario s

rr_{ij} Distance between donor i and mobile blood facility j

rb_{ik} Distance between donor i and local blood center k

rc Coverage distance of blood facilities

π_{s} Probability of scenario s occurrence

β	Referral rate: the rate at which services of local blood centers are directed to regional blood centers
M	A very large number

Decision variables:

X	An integer variable equal to the number of blood facilities
Z_{jlt}^{s}	A binary variable, equal to 1 if a blood facility is located at site *l* in period *t*–1,and moves to site *j* in period *t*; 0 otherwise.
Y_{ijt}^{s}	A binary variable, equal to 1 if blood facility *j* is assigned to donor *i* in period *t* under scenario *s*; 0, otherwise.
U_{ikt}^{s}	A binary variable, equal to 1 if local blood center *k* is assigned to donor *i* in period *t* under scenario *s*; 0, otherwise.
AL_{krt}^{s}	A binary variable, equal to 1 if local blood center *k* is allocated to regional blood center *r* in period *t* under scenario *s* ; 0 otherwise
QB_{ijkt}^{s}	Quantity of blood collected at blood facility *j* from donor *i* in period *t* to deliver to local blood center *k* under scenario *s*
QR_{ijrt}^{s}	Quantity of blood collected at blood facility *j* from donor *i* in period *t* to deliver to regional blood center *r* under scenario *s*
OQ_{ikt}^{s}	Quantity of blood collected at local blood center *k* from donor *i* in period *t* under scenario *s*
BTR_{krt}^{s}	Quantity of blood delivered from local blood center *k* to regional blood center *r* in period *t* under scenario *s*
QBH_{kht}^{s}	Quantity of transfused blood delivered from local blood center *k* to hospital *h* in period *t* under scenario *s*
QRH_{rht}^{s}	Quantity of transfused blood delivered from regional blood center *r* to hospital *h* in period *t* under scenario *s*
IB_{kt}^{s}	Blood inventory level at local blood center *k* at the end of period *t* under scenario *s*
IR_{rt}^{s}	Blood inventory level at regional blood center *k* at the end of period *t* under scenario *s*

The problem is formulated as a two-stage stochastic programming model using a set of disaster scenarios. In a two-stage programming approach (Birge and Louveaux, 2011), decision variables are divided into two categories: first-stage decisions and second-stage decisions. The first stage decisions are not reliant on the disaster scenario realization and can be taken before a scenario is realized. Second-stage decisions are scenario-dependent variables and are hence made post scenario realization. In our model, decision variable X (the number of blood facilities) is scenario-independent and hence its value can be determined in stage 1. The values of all other decision variables are determined in stage 2 depending on what disaster scenarios occurs.

3.3 Objective functions

The first objective function minimizes the expected cost of the supply chain. The supply chain cost components under each scenario include the cost of establishing blood facilities (EC), cost of moving mobile blood facilities (MC_s), operational cost (OC_s), transportation cost (TC_s) and inventory cost (IC_s), formulated in Equations (1)-(5).

$$EC(\text{cost of establishing mobile blood facilities}) = fX \tag{1}$$

$$MC_s(\text{cost of moving mobile blood facilities}) = \sum_{l\in J}\sum_{j\in J}\sum_{t\in T} v^s_{jlt} Z^s_{jlt} \tag{2}$$

$$\begin{aligned} OC_s(\text{operational cost}) &= \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} o^s_{ijt}\Big(\sum_{k\in K} QB^s_{ijkt} + \sum_{r\in R} QR^s_{ijrt}\Big) \\ &+ \sum_{k\in K}\sum_{t\in T} ob^s{}_{kt}\left(\sum_{i\in I}\sum_{j\in J} QB^s_{ijkt} + \sum_{i\in I} OQ^s_{ikt}\right) + \sum_{r\in R}\sum_{t\in T} or^s{}_{rt}\left(\sum_{i\in I}\sum_{j\in J} QR^s_{ijrt} + \sum_{k\in K} BTR^s_{krt}\right) \end{aligned} \tag{3}$$

$$\begin{aligned} TC_s(\text{transportation cost}) &= \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} ab^s_{jkt} QB^s_{ijkt} + \sum_{i\in I}\sum_{j\in J}\sum_{r\in R}\sum_{t\in T} ar^s_{jrt} QR^s_{ijrt} \\ &+ \sum_{k\in K}\sum_{r\in R}\sum_{t\in T} abr^s{}_{krt} BTR^s_{krt} + \sum_{k\in K}\sum_{h\in H}\sum_{t\in T} abh^s{}_{kht} QBH^s_{kht} + \sum_{r\in R}\sum_{h\in H}\sum_{t\in T} arh^s{}_{rht} QRH^s_{rht} \end{aligned} \tag{4}$$

$$IC_s\left(\text{inventory cost}\right) = \sum_{k\in K}\sum_{t\in T} hb_{kt} IB^s_{kt} + \sum_{r\in R}\sum_{t\in T} hr_{rt} IR^s_{rt} \tag{5}$$

The cost of establishing blood facilities in Equation (1) is obtained by multiplying the cost of establishing a mobile blood facility by the number of established blood facilities. Equation (2) formulates the cost of moving blood facilities from one site to another in different periods. Equation (3) expresses the sum of operational costs at mobile blood facilities, local blood centers and regional blood centers. Equation (4) calculates the total transportation costs including the transportation costs of delivering blood from mobile blood facilities to local and regional blood centers, from local blood centers to regional blood centers, and from local and regional blood centers to hospitals. Equation (5) shows the total cost of holding blood inventories at blood centers and regional blood centers. Using these cost components, the first objective function (cost function) is now formulated in Equation (6).

$$Min\, F_1 = EC + \sum_{s \in S} \pi_s \left(MC_s + OC_s + TC_s + IC_s \right) \tag{6}$$

The second objective function aims to minimize the average blood delivery time from local and regional blood centers to hospitals. The two components of the second objective function are formulated in Equations (7) and (8).

$$\begin{aligned} & TDB_s \left(\text{weighted-time for blood delivery through local blood centers}\right) \\ & = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} QB_{ijkt}^s \, tb_{jk} + \sum_{k \in K} \sum_{h \in H} \sum_{t \in T} QBH_{kht}^s \, tp_{kh} \end{aligned} \tag{7}$$

$$\begin{aligned} & TDR_s \left(\text{weighted-time for blood delivery through regional blood centers}\right) \\ & = \sum_{i \in I} \sum_{j \in J} \sum_{r \in R} \sum_{t \in T} QR_{ijrt}^s \, tr_{jr} + \sum_{k \in K} \sum_{r \in R} \sum_{t \in T} BTR_{krt}^s \, tc_{kr} + \sum_{k \in K} \sum_{h \in H} \sum_{t \in T} QRH_{rht}^s \, tq_{rh} \end{aligned} \tag{8}$$

Equation (7) shows the weighted travel time for the delivery of blood to hospitals through local blood centers, where blood quantities are considered as weights. The first term of Equation (7) corresponds to the time of blood delivery from mobile blood facilities to local blood centers and the second term concerns the time from local blood centers to hospitals. Equation (8) measures the weighted-time for blood delivery to hospitals through regional blood centers. The first two terms of Equation (8) capture the delivery time to regional blood centers from mobile blood facilities and local blood centers, respectively. The third term formulates the blood delivery time from regional blood centers to hospitals. Using Equations (7) and (8), we now formulate the second objective function in Equation (9).

$$Min\, F_2 = \sum_{s \in S} \pi_s \left(TDB_s + TDR_s \right) \tag{9}$$

3.4 Model constraints

The objective functions formulated in Section 3.3 are subject to the following constraints.

$$\sum_{j \in J} \sum_{l \in J} z_{jlt}^{s} \le X \qquad \forall t \in T, \forall s \in S \tag{10}$$

$$\sum_{l \in J} z_{jlt}^{s} \le 1 \qquad \forall j \in J, \forall t \in T, \forall s \in S \tag{11}$$

$$\sum_{l \in J} z_{ljt}^{s} \le \sum_{l \in J} z_{jl,t-1}^{s} \qquad \forall j \in J, \forall t \in T, \forall s \in S \tag{12}$$

$$Y_{ijt}^{s} \le \sum_{l \in J} z_{jlt}^{s} \qquad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \tag{13}$$

$$\sum_{\forall j \in J} \sum_{\forall k \in K} \sum_{\forall t \in T} QB_{ijkt}^{s} + \sum_{\forall j \in J} \sum_{\forall r \in R} \sum_{\forall t \in T} QR_{ijrt}^{s} + \sum_{k \in K} \sum_{t \in T} OQ_{ikt}^{s} \le m_i^s \qquad \forall i \in I, \forall s \in S \tag{14}$$

$$\sum_{i \in I} \sum_{k \in K} QB_{ijkt}^{s} + \sum_{i \in I} \sum_{r \in R} QR_{ijrt}^{s} \le b \qquad \forall j \in J, \forall t \in T, \forall s \in S \tag{15}$$

$$QB_{ijkt}^{s} \le MY_{ijt}^{s} \qquad \forall i \in I, \forall j \in J, \forall k \in K, \forall t \in T, \forall s \in S \tag{16}$$

$$QR_{ijrt}^{s} \le MY_{ijt}^{s} \qquad \forall i \in I, \forall j \in J, \forall r \in R, \forall t \in T, \forall s \in S \tag{17}$$

$$OQ_{ikt}^{s} \le MU_{ikt}^{s} \qquad \forall i \in I, \forall k \in K, \forall t \in T, \forall s \in S \tag{18}$$

$$rr_{ij} \times Y_{ijt}^{s} \le rc \qquad \forall i \in I, \quad \forall j \in J, \forall t \in T, \forall s \in S \tag{19}$$

$$rb_{ik} \times U_{ikt}{}^{s} \le rc \qquad \forall i \in I, \forall k \in K, \forall t \in T, \forall s \in S \tag{20}$$

$$\sum_{r \in R} AL_{krt}^{s} \le 1 \qquad \forall k \in K, \forall s \in S, t \in T \tag{21}$$

$$BTR_{krt}^{s} \le M\ AL_{krt}^{s} \qquad \forall k \in K, r \in R, \forall t \in T, \forall s \in S \tag{22}$$

$$BTR_{krt}^{s} \le \beta \left(\sum_{i \in I} \sum_{j \in J} QB_{ijkt}^{s} + \sum_{i \in I} OQ_{ikt}^{s} \right) \qquad \forall k \in K, \forall r \in R, \forall t \in T, \forall s \in S \tag{23}$$

$$IB_{k,t-1}^{s} + (1-\beta) \left(\sum_{i \in I} \sum_{j \in J} QB_{ijkt}^{s} + \sum_{i \in I} OQ_{ikt}^{s} \right) - \sum_{h \in H} QBH_{kht}^{s} = IB_{kt}^{s} \qquad \forall k \in K, \forall t \in T, \forall s \in S \tag{24}$$

$$IR^s_{r,t-1} + (\sum_{i\in I}\sum_{j\in J} QR^s_{ijrt} + \sum_{k\in K} BTR^s_{krt}) - \sum_{h\in H} QRH^s_{rht} = IR^s_{rt} \qquad \forall r\in R, \forall t\in T, \forall s\in S \tag{25}$$

$$\sum_{k\in K} QBH^s_{kht} + \sum_{r\in R} QRH^s_{rht} = d^s_{ht} \qquad \forall h\in H, \forall t\in T, \forall s\in S \tag{26}$$

$$IB^s_{kt} \le cb_k \qquad \forall k\in K, \forall t\in T, \forall s\in S \tag{27}$$

$$IR^s_{rt} \le cr_r \qquad \forall r\in R, \forall t\in T, \forall s\in S \tag{28}$$

$$Y^s_{ijt}, \mathrm{U}^s_{ikt}, AL^s_{krt} \in \{0,1\} \qquad \forall i\in I, \forall j\in J, \forall k\in K, \forall r\in R, \forall t\in T, \forall s\in S \tag{29}$$

$$QB^s_{ijkt}, QR^s_{ijrt}, QBH^s_{kht}, QRH^s_{rht}, BTR^s_{krt}, IB^s_{kt}, IR^s_{rt}, OQ^s_{ikt} \ge 0 \qquad \forall i\in I, \forall j\in J, \forall k\in K, \forall r\in R, \forall t\in T, \forall s\in S \tag{30}$$

$$X \text{ Integer} \tag{31}$$

Constraint (10) ensures that the number of mobile facilities in each period does not exceed the number of established blood facilities. Constraint (11) enforces locating no more than one mobile facility at each site. Constraint (12) makes sure that mobile facilities do not move to a location where a facility has been located before. Constraint (13) ensures that donors can only be assigned to open facilities. Constraint (14) expresses the capacity of blood supply by each donor group. Constraint (15) limits the capacity of blood collection at mobile blood facilities. Constraints (16) and (17) ensure the donated blood cannot be transported from a mobile facility that is not assigned to that donor group. Constraint (18) avoids collecting blood at local blood centers from donor groups not assigned to those blood centers. Constraints (19) and (20) ensure that mobile blood facilities and local blood centers only accept donors within their service area. Constraint (21) enforces that each local blood center is assigned to one regional blood center. Constraint (22) ensures that blood cannot be transported from a local blood center to a regional blood center which is not assigned to it. Constraint (23) shows that a local blood center has to direct β percent of their transfusion services to regional blood centers. Constraints (24) and (25) represent blood inventory balance constraints at local and regional blood centers, respectively. Constraint (26) ensures that blood demands in hospitals are fulfilled under each scenario. Constraints (27) and (28) express the capacities for storing blood at local and regional blood centers, respectively. Constraints (29)-(31) define the eligible domains of the decisions variables.

4. A Hybrid Solution Method

The bi-objective model presented in Section 3 can be transformed into a single-objective model using the co-called ε-constraint method. Solving the resulting single-objective model usually takes an excessively long time (even for average size problems) using the standard solution approaches. A Lagrangian relaxation approach can be utilized to solve this model within a reasonable length of time. Therefore, the hybrid solution method is made of combining the ε-constraint method and a Lagrangian relaxation method.

4.1 Stage 1: Conversion to a single-objective model

We use an ε-constraint method to convert the bi-objective model presented in Section 3 into a single-objective optimization model. The ε-constraint method, first introduced by (Haimes et al., 1971), is one of the most popular multi-objective optimization programming methods. In the ε-constraint method, all objectives except for one are converted into constraints and an upper bound limit is set for each constraint. The method works by pre-defining a virtual grid in the objective space and solving different single-objective problems constrained to each grid cell. Thus, all Pareto-optimal solutions can be obtained if this grid is fine enough such that at most one Pareto-optimal solution is contained in each cell (Laumanns et al., 2006; Mavrotas, 2009). The idea is to overcome the complexity of solving a multi-objective model by minimizing or maximizing one objective at a time and expressing the other objectives in form of inequality constraints. Let us consider a multi objective problem with K objective functions as below:

$$Min_{X \in \chi} \left\{ F(x) = (F_1(x), F_2(x), \ldots F_K(x)) \right\}, \tag{32}$$

where X is the vector of decision variables, $F(x)$ is the vector of K objective functions, and χ is the space of feasible solutions. Based on the ε-constraint method, the multi-objective problem in Equation (32) can be converted into a single-objective model in Equations (33) and (34) in which only the primary objective function $F_k(x)$ is minimized and the remaining objective functions are expressed as model constraints with enforcing upper bounds.

$$Min_{X \in \chi} F_k(x) \tag{33}$$

$$\textit{subject to}$$
$$F_i(x) \le \varepsilon_i \qquad \forall i \in \{1, 2, ..., K\} \setminus \{k\} \tag{34}$$

Applying the ε-constraint method to our bi-objective model, we keep the first objective function (cost function in Equation (6)) as the primary objective function and transform the second objective function (time function in Equation (9)) into a constraint with upper bound ε, hereafter called *time tolerance* (Demand*Hour). Thus, the bi-objective model is now converted into the following single-objective model:

$$\text{Min } F_1 \tag{35}$$

$$\textit{Subject to}$$
$$\sum_{s \in S} \pi_s (TDB_s + TDR_s) \le \varepsilon \tag{36}$$

Constraints (10)-(31)

4.2 Stage 2: Solving the single-objective model

The single objective model presented in Section 4.1 is a large mixed-integer programming problem that resembles an Uncapacitated Facility Location Problem (UFLP). Since the UFLP is NP-hard (see Krarup and Pruzan (1983)), it is not possible to solve the large problem instances in polynomial time using standard solution methods (Hinojosa et al., 2008). For this reason, we adopt a Lagrangian relaxation approach to solve the unified optimization model. Lagrangian relaxation is a powerful solution method with demonstrated applications in solving supply chain combinatorial optimization problems (see for example Diabat et al. (2014), Kang and Kim (2012), Badri et al. (2013) and Jayaraman and Pirkul (2001)). The method is capable of providing upper and lower bounds of an optimal objective value allowing a decision maker to estimate the quality of solutions and realize how far a best found feasible solution is from the optimality (Fisher, 2004).

The Lagrangian relaxation method that we adopt in this paper operates in three steps, (1) finding a lower bound for optimal solutions, (2) obtaining an upper bound for optimal solutions, and (3) updating the upper and lower bounds if they are not sufficiently close. The steps are iterated until the lower and upper bounds reach certain closeness. We now discuss these three steps for solving the unified optimization model introduced in Section 4.1.

4.2.1 Finding a lower bound

A lower bound is obtained by relaxing few constraints that make the problem easier to solve even if it causes infeasibility (see Fisher (2004)). In this case, we choose to relax constraints (22) and (23) as the resulting model will be easier to solve. Relaxing these constraints produces the following Lagrangian dual problem:

$$\begin{aligned} & Min\ L(u^1_{krts}, u^2_{krts}) = EC + \sum_{s\in S} \pi_s \left(MC_s + OC_s + TC_s + IC_s \right) + \\ & \sum_{k\in K}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S} u^1_{krts} \left(BTR^s_{krt} - M\ AL^s_{krt} \right) + \\ & \sum_{k\in K}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S} u^2_{krts} \left(BTR^s_{krt} - \beta \left(\sum_{i\in I}\sum_{j\in J} QB^s_{ijkt} + \sum_{i\in I} OQ^s_{ikt} \right) \right) \end{aligned} \tag{37}$$

Subject to: Constraints (10) to (21), constraints (24) to (31), and constraint (36)

Where u^1_{krts} and u^2_{krts} denote non-negative Lagrange multipliers. For fixed values of the Lagrange multipliers, u^1_{krts} and u^2_{krts}, we aim to minimize Equation (37) over decision variables $Y^s_{ijt}, \mathrm{U}^s_{ikt}, AL^s_{krt}, X, QB^s_{ijkt}, QR^s_{ijrt}, QBH^s_{kht}, QRH^s_{rht}, BTR^s_{krt}, IB^s_{kt}, IR^s_{rt}$ and OQ^s_{ikt}. Optimal objective value of the Lagrangian dual problem (37) provides a lower bound to the problem (Fisher, 2004).

4.2.2 Finding an upper bound

In most cases, the solution obtained from solving Lagrangian dual problem (37) is infeasible due to relaxing constrains (22) and (23). A feasible solution can be found as follows. We solve the minimization model (35) under constraints (10)-(31) and (36) when setting the decision variables X equal to optimal values obtained from solving the Lagrangian dual problem (37). The resulting feasible solution provides an upper bound for the model (35).

4.2.3 Updating lower and upper bounds

If the obtained lower bound is equal to the upper bound within some pre-specified tolerance, a desirable solution to model (35) under constraints (10)-(31) and (36) is already found. Otherwise, the Lagrange multipliers u^1_{krts} and u^2_{krts} are updated and consequently the new lower and upper bounds are found. We assign values to the Lagrange multipliers at iteration n+1, using subgradient optimization described by Fisher (2004) as follows.

$$u^{1,n+1}_{krts} = \max\left\{0, u^{1,n}_{krts} - stepsize1^n\left(BTR^s_{krt} - M\ \ AL^s_{krt}\right)\right\} \tag{38}$$

$$u^{2,n+1}_{rts} = \max\left\{0, u^{2,n}_{rts} - stepsize2^n\left(BTR^s_{krt} - \beta\left(\sum_{i\in I}\sum_{j\in J} QB^s_{ijkt} + \sum_{i\in I} OQ^s_{ikt}\right)\right)\right\} \tag{39}$$

Where n denote the number of iteration and $stepsize1^n$ and $stepsize2^n$ are defined as below.

$$Step\ size1^n = \frac{\alpha^n\left(UP - LB^n\right)}{\sum_{r\in R}\sum_{k\in K}\sum_{t\in T}\sum_{s\in S}\left(BTR^s_{krt} - M\ \ AL^s_{krt}\ \ \right)^2} \tag{40}$$

$$Step\ size2^n = \frac{\alpha^n\left(UP - LB^n\right)}{\sum_{r\in R}\sum_{k\in K}\sum_{t\in T}\sum_{s\in S}\left(BTR^s_{krt} - \beta\left(\sum_{i\in I}\sum_{j\in J} QB^s_{ijkt} + \sum_{i\in I} OQ^s_{ikt}\right)\right)^2} \tag{41}$$

We note that UP is the best found upper bound and LB^n is the lower bound obtained at iteration n. We initially set α = 2 and if no improvement in LB is achieved for four consecutive iterations, then α is halved. This process continues until a feasible solution with the desired tolerance is obtained or the minimum value of the *step-size* is reached.

5. Computational Results

We design a set of test experiments to (1) evaluate the performance of the proposed hybrid solution method, (2) investigate possible tradeoffs between supply chain cost and delivery time, and (3) examine the benefits of the two-stage stochastic programming approach by comparing its performance against that of an expected value approach. Three random datasets are generated with different sizes as shown in Table 1. General Algebraic Modeling System (GAMS) – version 24.1 – is used for problem modeling and optimization. GAMS utilizes a language compiler and a range of integrated high-performance solvers for modeling and solving complex, large scale optimization problems.

Table 1. Characteristics of the three datasets used in all experiments

	$\|I\|$	$\|J\|$	$\|K\|$	$\|R\|$	$\|H\|$	$\|T\|$	$\|S\|$
Dataset 1	6	4	3	3	3	3	5
Dataset 2	10	8	5	5	10	5	10
Dataset 3	12	10	8	8	15	7	15

5.1 The initial numerical results

For the three datasets, Table 2 presents the numerical results obtained using the hybrid solution method at different referral rate (β) and time tolerance (ε) values. From left to right, the columns named "UB" and "LB" show respectively the upper and lower bounds obtained from the Lagrangian method. The column labelled "Gap" is the percentage difference between the upper bound and lower bound, which is calculated from $\frac{UB - LB}{UB} \times 100$. Model runtime is given in the next column. Whilst GAMS was unable to provide feasible solutions for datasets 2 and 3 within 48 hours of model runtime, the hybrid solution method was capable of reaching optimal solutions in all the instances within a reasonable length of time (given the strategic type of decisions facing). High-quality solutions that are close-to-optimal could be obtained within a shorter runtime by setting the termination condition at some values for GAP, rather than looking for zero-gap solutions.

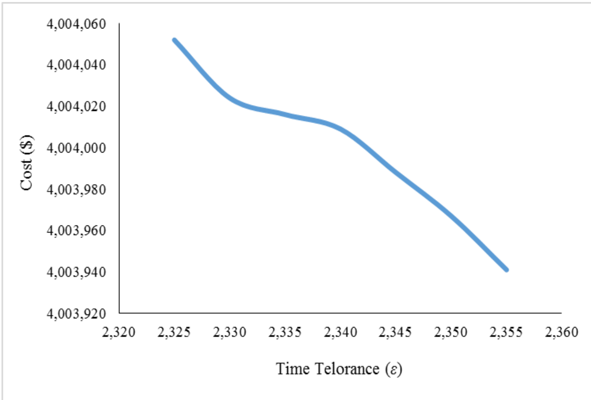
Table 2. The numerical results for all datasets

Dataset	β	ε	LB	UP	GAP	Runtime
Dataset 1	0.1	2612	4002367	4002367	0.00	0:00:21
	0.2	2530	4002855	4002855	0.00	0:00:17
	0.3	2473	4003282	4003282	0.00	0:00:19
	0.4	2419	4003728	4003728	0.00	0:00:13
	0.5	2374	4004194	4004194	0.00	0:00:19
	0.6	2333	4004620	4004620	0.00	0:00:41
	0.7	2264	4005106	4005106	0.00	0:00:52
	0.8	2212	4005536	4005536	0.00	0:00:24
	0.9	2170	4005962	4005962	0.00	0:01:02
Dataset 2	0.1	125237	29263118	29263118	0.00	3:51:39
	0.2	127124	33011821	33011821	0.00	4:10:12
	0.3	130098	35547428	35547428	0.00	1:45:19
	0.4	133374	36755610	36755610	0.00	2:49:38
	0.5	136749	37137913	37137913	0.00	0:31:59
	0.6	141197	36608040	36608040	0.00	0:01:15
	0.7	147235	35430071	35430071	0.00	0:06:18
	0.8	152894	34775230	34775230	0.00	0:16:26
	0.9	159148	32524430	32524430	0.00	0:23:10
Dataset 3	0.1	254064	116010000	116010000	0.00	5:22:39
	0.2	269348	134395600	134395600	0.00	2:10:02
	0.3	292887	149218300	149218300	0.00	3:18:36
	0.4	318227	161072130	161072130	0.00	5:51:23
	0.5	354652	162926100	162926100	0.00	7:25:52
	0.6	391540	150705200	150705200	0.00	1:33:30
	0.7	419598	135299100	135299100	0.00	0:47:16
	0.8	440658	123380000	123380000	0.00	4:08:44
	0.9	457410	114713900	114713900	0.00	5:26:50

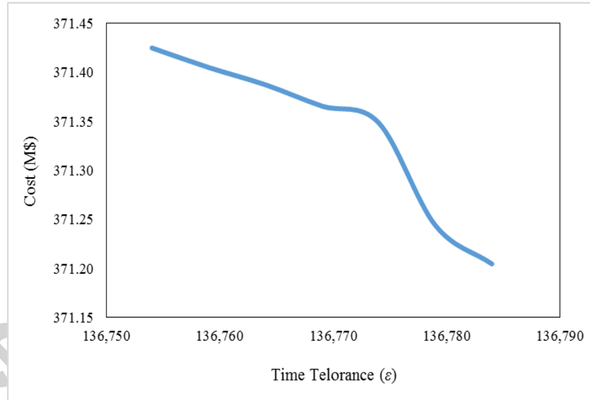
5.2 Tradeoff between cost and delivery time

We now examine the impact of varying time tolerance (ε) on the supply chain costs. Such analyses enable a decision maker to explore the tradeoff between supply chain cost and delivery time (noting that ε represents the maximum blood delivery time). For the three datasets, the tradeoffs between cost and delivery time (Demand*Hour) are illustrated in Figures 1. A first observation is that for all three datasets the supply chain cost decreases as time tolerance rises. This finding could be expected as faster delivery does not come free. What is interesting is the pattern of cost change for different datasets and at different ranges of time tolerance. A decrease in the value of ε causes a relatively linear total supply chain cost increases in all instances, but the line steepness varies from one dataset to another and for different ranges of ε values. In other words, the relationship between cost and delivery time is a function of supply chain size and the range of changes in time tolerance. Note that supply chain size is represented by different datasets where dataset 3 corresponds to the largest network. Another insight from these findings is that there may be more potential to gain significant delivery speed improvements at only minor increases in supply chain costs. For example, for dataset 1, a minor increase in supply chain cost results when the time tolerance reduces from 2,335 to 2,330 (compare this to the next range of time tolerance values when ε changes from 2,330 to 2,325).

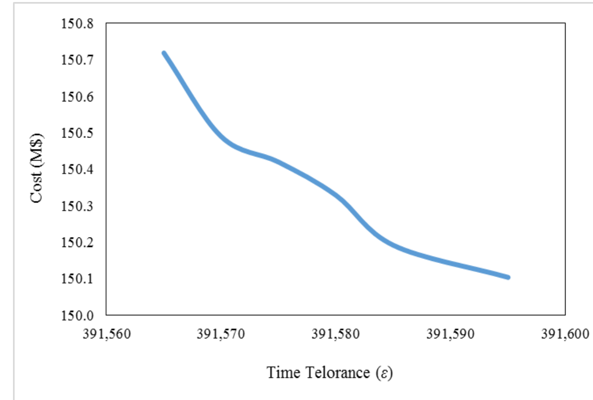
Overall, Figure 1 suggests that compromise solutions may exist between supply chain cost and time tolerance. In the following sections, we complete sensitivity analysis experiments seeking opportunities to simultaneously improve the supply chain cost and delivery performance.



1a. The tradeoff curve for dataset 1



1b. The tradeoff curve for dataset 2



1c. The tradeoff curve for dataset 3

Figure 1. Tradeoff between supply chain cost and delivery time for datasets 1-3

5.3 Sensitivity analysis on the referral rate

This section aims to examine the changes in supply chain configuration, cost, and delivery performance as the referral rate is increased. A larger referral rate means that more transfusion services are directed to regional blood centers. Note that a referral rate of 0.3 implies that 70% of transfusion operations are completed in local blood centers and 30% referred to regional blood centers. For the three datasets, Table 3 shows optimal supply chain cost and configuration at different referral rates. The experiments are completed for fixed time tolerance of the three datasets (i.e. a fixed service level). What is evident in these results is that greater referral rates result in increased supply chain costs and more open facilities are required to maintain the same service level. Thus, it is more worthwhile to reduce the referral rate by improving the dependency of local blood centers to regional centers. The impacts on supply chain cost and configuration are more pronounced in larger datasets.

For a budget-constrained situation, Table 4 shows the impacts of increased referral rates on the blood delivery performance. We observe that a larger referral rate results in an increased delivery time, mainly due to the additional transportation time required for completing the blood transfusion in multiple locations. The delivery performance can be improved as much as 45% by choosing a very small referral rate. Similar to the cost performance in Table 3, changes in delivery time performance are more pronounced with larger datasets. What is obvious from Tables 3 and 4 is that establishing more independent local blood centers, less reliant on the services of regional centers, is an efficient (cost measure) and effective (time measure) strategy.

Performing more transfusion operations in local blood centers to reduce the referral rate may require additional investment to expand the transfusion operations in local blood centers. The investment margins can be drawn from the corresponding cost savings. For example, for the largest problem (dataset 3), the supply chain yields a cost saving of $14,049,000 (i.e. $100,793,000 minus $114,842,000), equal to 12.2% of the overall supply chain cost, when the referral rate reduces from 40% to 30%. This cost saving is the marginal investment the supply chain will be willing to pay to reduce the referral rate by 10%. We recognize that such findings may be problem-specific, but here we have tried to illustrate how the model and solution method introduced in this paper can be used for analyzing such a tradeoff.

Table 3. The impact of varying referral rate (β) on supply chain cost and optimal number of blood facilities at a fixed time tolerance

	Dataset 1			Dataset 2			Dataset 3		
Referral Rate	Total cost ($)	Cost difference (%)	Number of facilities	Total cost ($)	Cost difference (%)	Number of Facilities	Total Cost ($)	Cost difference (%)	Number of Facilities
0.9	4,005,132		2	41,598,907		20	140,612,000		34
0.8	4,004,813	0.01	2	38,214,339	8.14	18	137,322,000	2.34	33
0.7	4,004,410	0.02	2	35,433,130	14.82	17	135,300,000	3.78	32
0.6	4,003,726	0.04	2	35,085,880	15.66	17	134,781,000	4.15	32
0.5	4,003,348	0.04	2	34,725,050	16.52	16	128,919,000	8.32	31
0.4	4,003,058	0.05	2	33,551,090	19.35	16	114,842,000	18.33	28
0.3	4,002,690	0.06	2	32,015,610	23.04	15	100,793,000	28.32	24
0.2	4,002,278	0.07	2	29,394,190	29.34	14	92,233,100	34.41	22
0.1	4,001,896	0.08	2	26,784,300	35.61	13	86,092,200	38.77	21

Table 4. The impact of varying referral rate (β) on delivery time and optimal number of blood facilities at a fixed supply chain cost

	Dataset 1			Dataset 2			Dataset 3		
Referral Rate	Total Time	Time difference (%)	Number of Facilities	Total Time	Time difference (%)	Number of Facilities	Total Time	Time difference (%)	Number of Facilities
0.9	2,472		4	156,710		16	461,851		22
0.8	2,425	1.90	5	150,813	3.76	21	440,345	4.66	22
0.7	2,368	4.21	5	145,321	7.27	21	418,231	9.44	24
0.6	2,314	6.39	7	140,680	10.23	23	390,522	15.44	25
0.5	2,269	8.21	7	135,565	13.49	23	345,612	25.17	27
0.4	2,218	10.28	7	131,920	15.82	24	303,901	34.20	30
0.3	2,159	12.66	7	129,503	17.36	26	285,673	38.15	32
0.2	2,107	14.77	10	126,946	18.99	27	270,865	41.35	33
0.1	2,065	16.46	10	125,163	20.13	28	253,955	45.01	33

5.4 Sensitivity analysis on the storage capacity of facilities

We now complete a sensitivity analysis to examine whether adjustments in facility storage capacity can be used as a strategy to improve supply chain cost and service level. Figure 2 illustrates changes in supply chain cost over a range of storage capacity levels. A general observation is that increased storage capacity in blood facilities results in reduced supply chain cost. Similar patterns can be observed for the three datasets; however, the magnitude of cost savings is not proportionate to the network size (i.e. the curve for dataset 3 is steeper than that of dataset 1 which in turn is steeper than dataset 2 curve). The cost savings (curve steepness) is indeed a function of "inventory cost over transportation cost" ratio. Dataset 3 holds the lowest ratio implying a greater transportation cost and smaller inventory cost which allows the network to take advantage of increased capacity of facilities to reduce the frequency and quantity of shipments between supply chain nodes.

No significant impact on the supply chain delivery time could be observed for the same changes in facility capacity. This is unlike changes in referral rate which was shown to significantly influence both supply chain cost and delivery time performance.

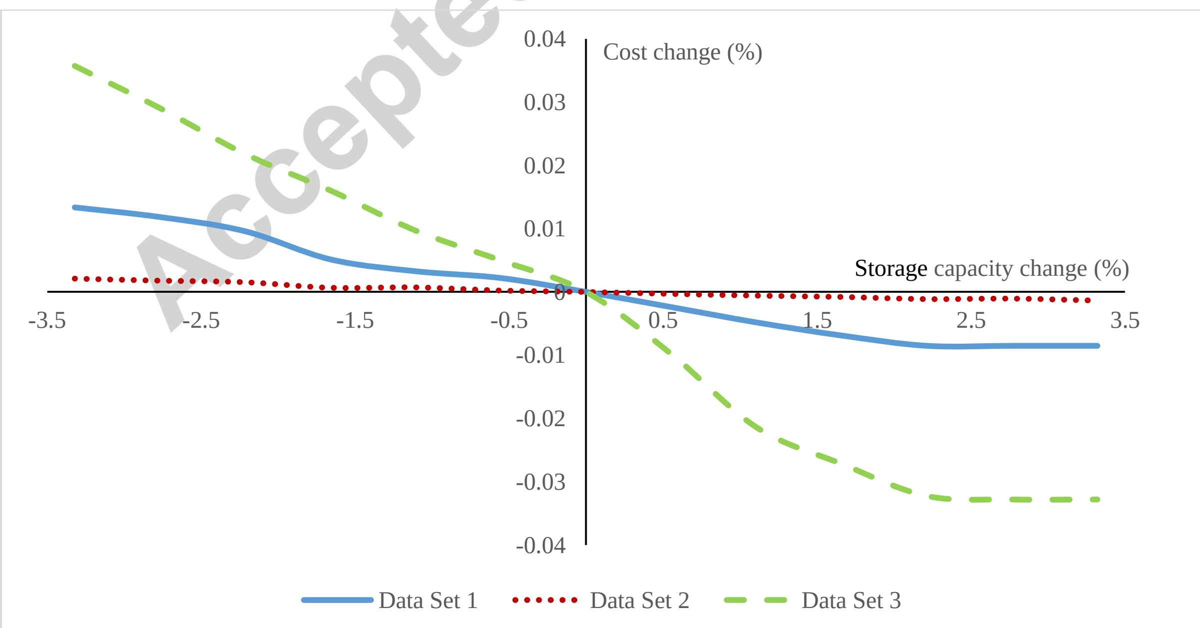


Figure 2. The impact of facility capacity change on the total supply chain cost

5.5 Benefit of facility location mobility

This section aims to investigate how the supply chain benefits from a facility location mobility feature. For this experiment, we compare the supply chain cost in two situations: (1) static facility location where the locations of blood facilities are fixed in all planning periods, and (2) dynamic facility location where facilities are mobile, so they can be relocated at each period based on the network requirements. Obviously, a dynamic network offers more supply flexibility and hence results in smaller transportation and inventory holding costs. This makes a dynamic facility location a cheaper option, if the "cost of flexibility" (i.e. the costs associated with frequent relocation of facilities) is not taken into consideration. For the three datasets, Figure 3 illustrates the marginal cost differences between the static and dynamic facility location options over a range of referral rates. We observe that cost saving from a dynamic facility location option would be as large as 10% at greater referral rates. A greater referral rate implies more frequent travels from local to regional blood centers. The need for these frequent trips is less when facilities are mobile and can be positioned in more convenient locations. The reduced transportation cost is the primary advantage of the dynamic facility location option.

The cost difference between static and dynamic facility location options can be used as an estimation tool for determining the cost of flexibility. For example, for dataset 2 at the referral rate of 0.6, one would be willing to accept a marginal supply chain cost increase of 9% to improve the network flexibility. That is, the conversion from a static to dynamic facility location option would only be worthwhile if the associated facility relocation costs do not add more than 9% to the supply chain costs. It should be noted that at each referral rate, the cost difference is obtained through a tradeoff analysis between the two ratios of "transportation cost to total cost" and "cost of moving facilities to total cost".

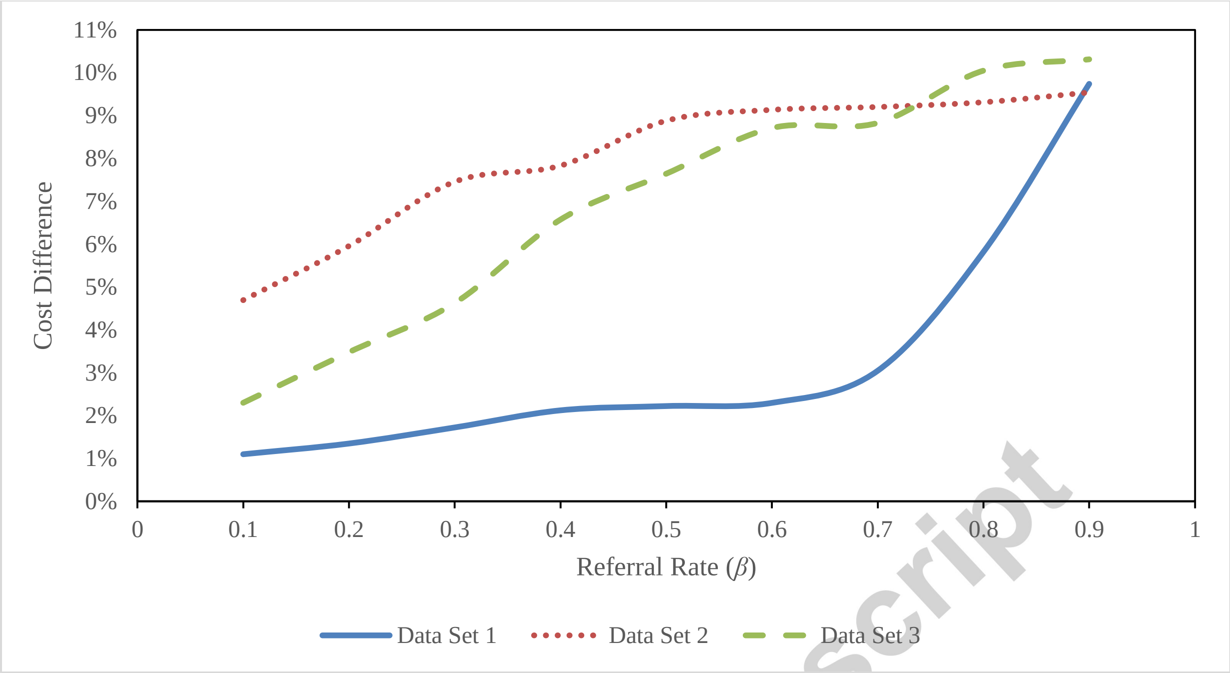


Figure 3. The percentage of cost saving obtained from a facility mobility option

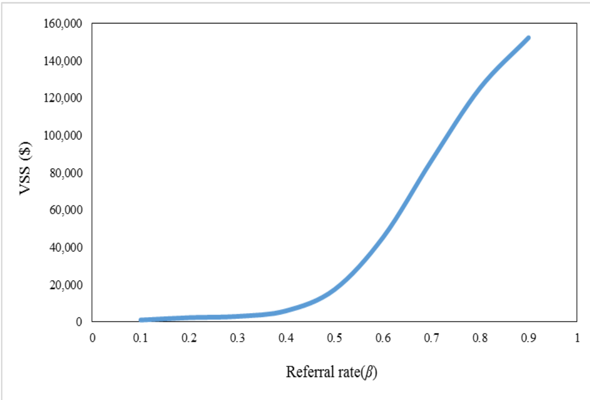
5.6 Benefit of stochastic programming approach

One way to investigate the benefits of the proposed two-stage stochastic programming approach is to compare its performance against that of an expected value approach. To do so, we use a measure called Value of the Stochastic Solution (VSS) introduced by Birge (1982). VSS can be formulated as:

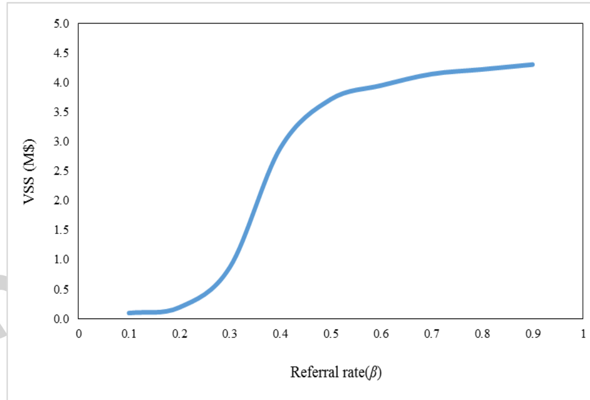
$$VSS = EEV - RP, \tag{42}$$

where *EEV* and *RP* denote the objective values under expected value and stochastic programming approaches, respectively. *RP* is the optimal objective value of the model (35) under constraints (10)-(31) and (36). To obtain *EEV*, the expected values of uncertain parameters are first calculated. Then, model (35) is solved under constraints (10)-(31) and (36) by setting the values of the random parameters equal to their expected values. The solution obtained from solving this model provides the optimal number of blood facilities (*X*) for the expected value approach. Finally, model (35) is solved again under constraints (10)-(31) and (36) by using original demand data and setting the number of mobile blood facilities equal to the optimal number of blood facilities (X) obtained in the previous step.

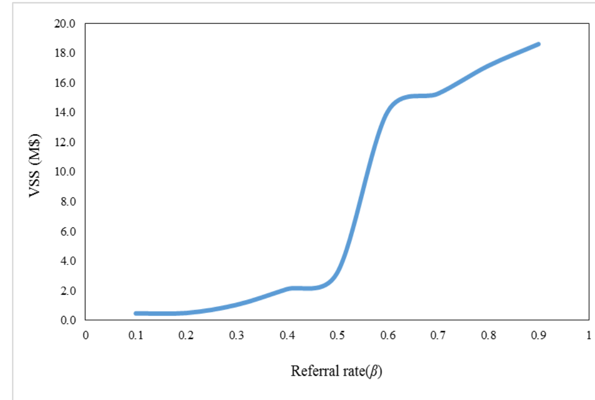
For our three datasets, Figures 4 show changes in VSS values over a range of referral rates (β). For all datasets and regardless of the β value, these results indicate that the stochastic programming approach clearly outperforms an expected value approach, evidenced by the positive values for VSS in all figures (from Equation (42), a positive value for VSS implies that $EEV > RP$). This experiment can also be treated as a sensitivity analysis for examining the value of a stochastic programming over a range of referral rates. The benefits of the stochastic programming approach increases as the referral rate gets larger. The cost benefits do not follow a similar pattern in different datasets. For example, Figure 4b shows that for dataset 2, greater benefits are obtained at initial increases in the referral rate. This is not the case for datasets 1 and 3 where the stochastic programming approach has a stronger dominance at larger β values. Overall, the proposed stochastic programming approach does show a clear dominance over an expected value approach, yet the scale of this dominance is a function of supply chain size and its parametric properties, including cost parameters.



4a. VSS results for dataset 1



4b. VSS results for dataset 2



4c. VSS results for dataset 3

Figure 4. The value of stochastic programming approach for the three datasets

6. Conclusions

Natural disasters are increasing in frequency and intensity and their direct human impacts are pronounced more than ever before. History also records a continuous stream of anthropogenic catastrophes causing thousands of deaths and injuries every year. The emergency supply of blood in such disasters has proved challenging. This paper contributes to this area of research by presenting a stochastic bi-objective supply chain network design model for the efficient and timely supply of blood in disasters. The first objective minimizes the overall supply chain costs (efficiency factor) and the second objective minimizes the blood delivery time (effectiveness factor). In the proposed two-stage stochastic model, stage 1 decisions (the number of blood facilities to open) are made when no knowledge of disaster is available, and stage 2 decisions (blood collection and transportation quantities and inventory levels) are determined when a disaster scenario is realized.

A hybrid solution approach was presented that combines an ε-constraint method with a Lagrangian relaxation approach. The ε-constraint method transforms the bi-objective model into an equivalent single-objective model for which the Lagrangian relaxation approach can find an optimal solution. The numerical results provided a number of insights. Particularly, we find that (1) the proposed solution approach is able to find quality solutions to problems of different sizes within reasonable model runtimes, (2) the stochastic programming approach outperforms an expected value approach regardless of the problem size and complexity, (3) the relationship between cost and delivery time is a function of supply chain size and time tolerance, (4) adjustments in referral rate (the rate at which transfusion services are directed to regional blood centers) and the capacity of blood facilities can be used to improve the supply chain cost and delivery time performance, and (5) the proposed model and solution technique can be used for cost/benefit analysis to identify the areas and operations along the supply chain where investments can be made for improved supply chain efficiency and effectiveness.

The modeling effort in this paper can set the stage for additional research in the area of blood supply chain management. The call for increased management research in the area of disaster relief operations management has been widely acknowledged (Caunhye et al., 2012; Starr and

Van Wassenhove, 2014; Wassenhove, 2006). Despite this, scanty modeling efforts exist to address serious challenges facing governments and humanitarian aid agencies. Not only can such modeling efforts save lives and reduce suffering for people affected by disasters, but the lessons learnt can also provide insights for the design and management of more responsive supply chains when facing supply and demand disruptions.

Future research could investigate the application of the model and solution method presented in this paper to managing actual blood supply chain challenges. The academic research currently suffers from the absence of such all-inclusive disaster data. Given the reducing funding for humanitarian and disaster relief efforts and hence shrinking infrastructure and network design budgets, a direction for future work could be on prioritizing supply chain operations to which additional funds should be assigned for designing more resilient and responsive blood supply networks. In addition, more sophisticated models and solution techniques are required for delivery of relief supplies when disasters affect multiple facilities in a healthcare system, as is often the case. In addition, the clear focus of our study was on the quick response phase of disaster management; that is, the emergency supply of blood products immediately after disasters. Future research can complete similar analysis and tradeoff investigations for other disaster management phases, which may involve the incorporation of additional factors and performance measures. For example, the more explicit consideration of blood perishability can be of paramount importance in the reconstruction phase of disaster management.

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Highlights

- A stochastic bi-objective supply chain design model for supply of blood in disasters;
- Considering efficiency (cost) and effectiveness (delivery time) goals;
- Modeling effort motivated by real world parameters, variable and constraints;
- A solution approach combining ε -constraint and Lagrangian relaxation methods;
- Managerial insights and practical implications obtained from the numerical results.